

Flower Classification

Franko Ndou



BlossomTech

- Floral Focused AI Tech Startup
- Creates ML models to support its other endeavors (App development and E-Commerces)
- Core mission to pursue innovation to further understand the beauty of nature



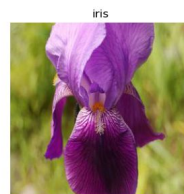
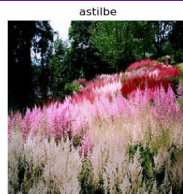
Business Problem

- BlossomTech: Tech startup based in NYC
- The target sectors include agriculture, horticulture, and e-commerce.
- Objective: Develop an AI model to supersede current slow and error-prone identification methods



Dataset

- Utilizing the "Flower Classification" dataset from Kaggle.
- Features diverse flower images across 14 species, each labeled for supervised learning.
- Dataset includes training and validation (used as test data) sets.
- Total of approximately 13,000 images, with 207 images in each test folder and 500-800 images in each training folder.



Architecture

- Sequential neural network with 3 convolutional layers, pooling, batch normalization, 1 dense hidden layer, and an output layer.
- Utilizes ReLU and Softmax activations, dropout regularization.
- Configured for classifying images into 14 categories.

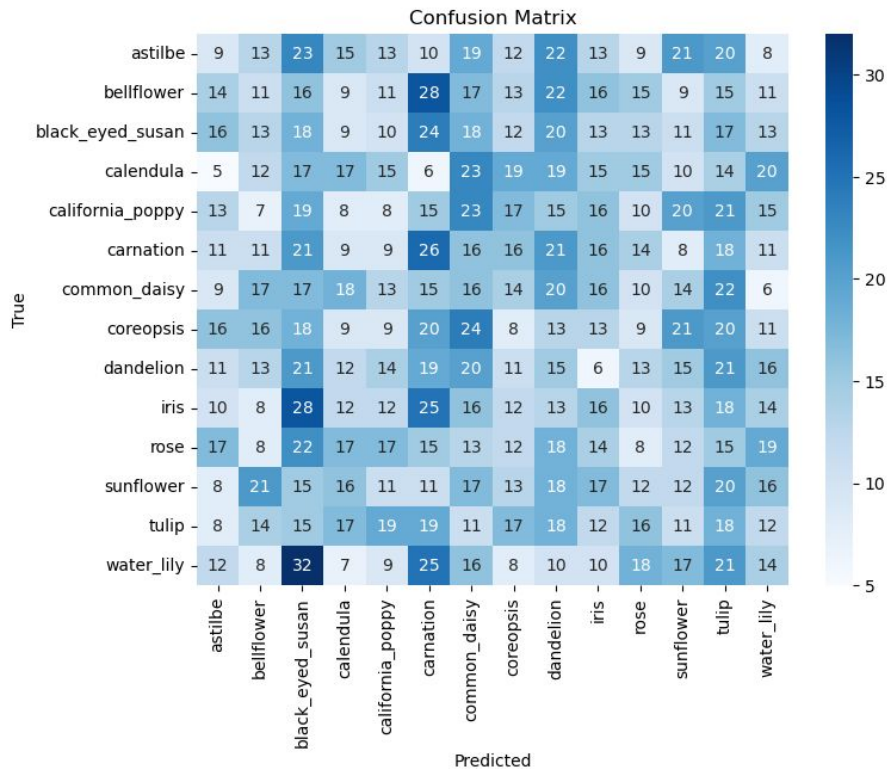
```
# Function to create a Keras model
def create_model(optimizer='adam', dropout_rate=0.5):
    model = Sequential()
    model.add(Conv2D(16, (3, 3), 1, activation='relu', input_shape=(128, 128, 3)))
    model.add(MaxPooling2D())
    model.add(BatchNormalization())
    model.add(Conv2D(32, (3, 3), 1, activation='relu'))
    model.add(MaxPooling2D())
    model.add(BatchNormalization())
    model.add(Conv2D(16, (3, 3), 1, activation='relu'))
    model.add(MaxPooling2D())
    model.add(BatchNormalization())
    model.add(Flatten())
    model.add(Dense(256, activation='relu'))
    model.add(Dropout(dropout_rate))
    model.add(Dense(14, activation='softmax'))

    model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=['accuracy'])

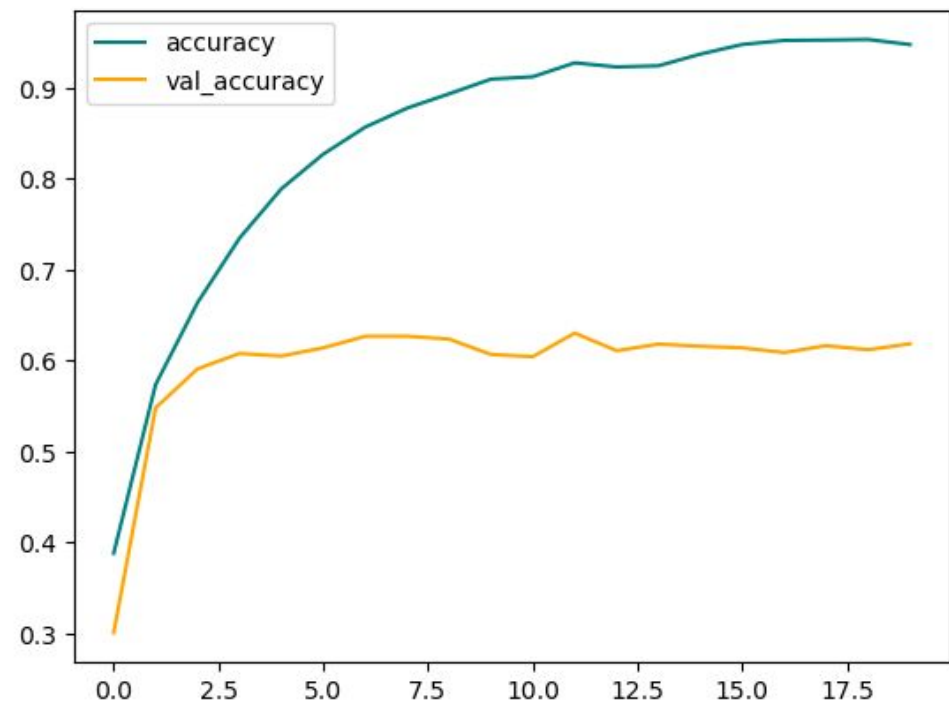
    return model
```

Baseline Model (Pre-Augmentation)

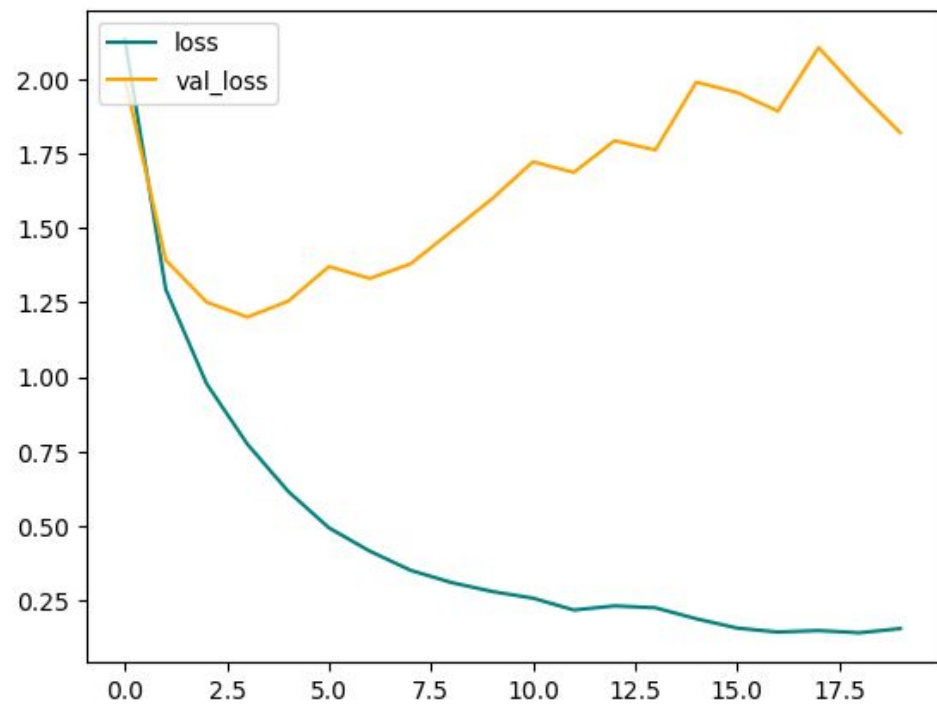
- Started with poor baseline model performance: only 59% accuracy.
- Faced significant overfitting issues.
- Accuracy and loss scores indicated severe overfitting.



Accuracy

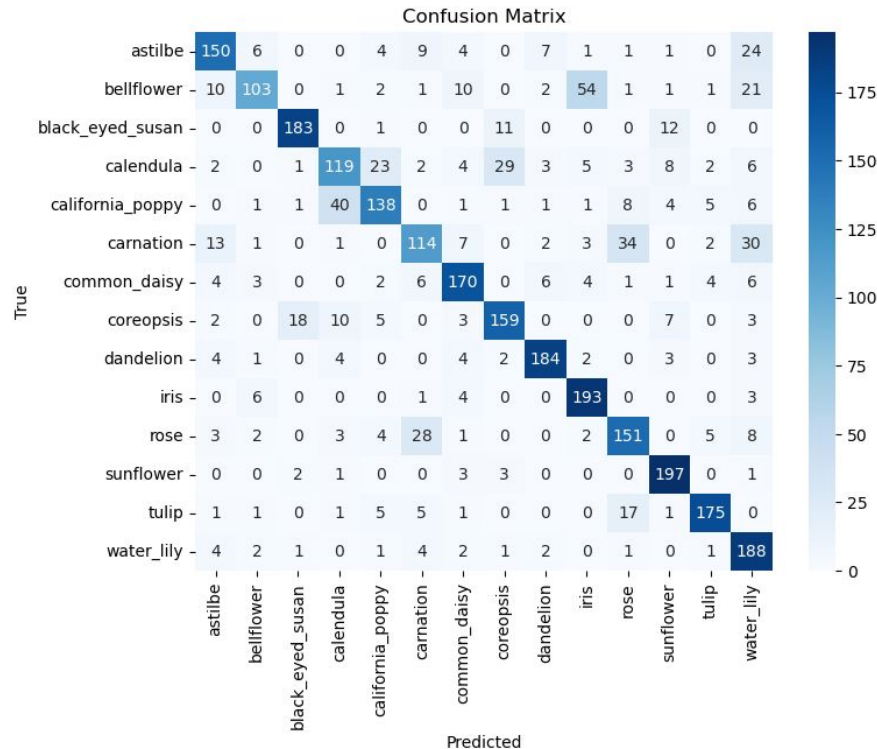


Loss



Baseline Model (Post-Augmentation)

- Model accuracy increased significantly from 59% to 76.7%.
- Notable reduction in overfitting.
- Enhanced generalization of data patterns by the model.



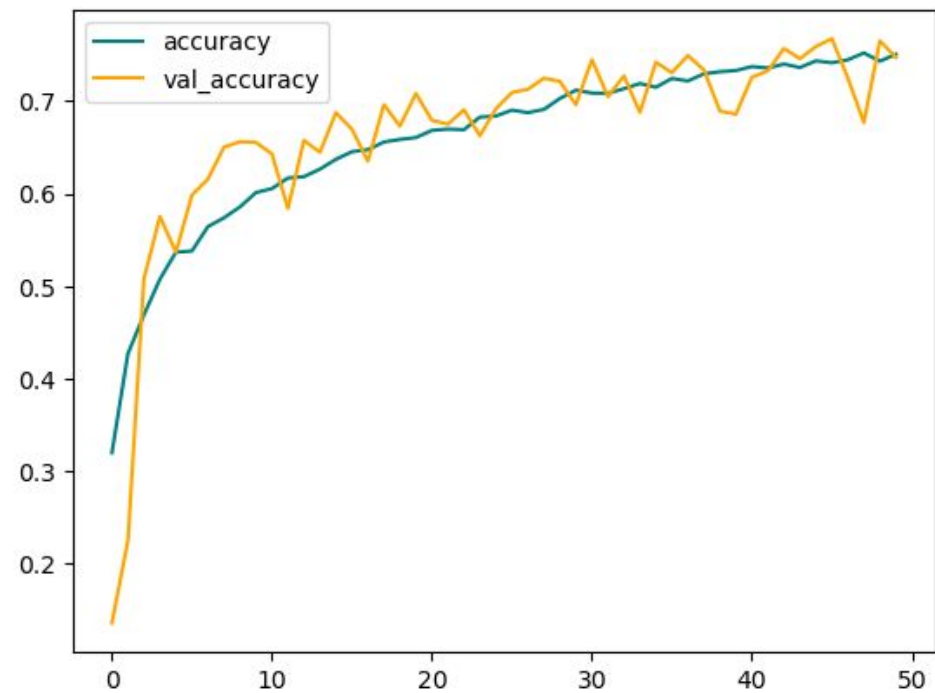
Calendula



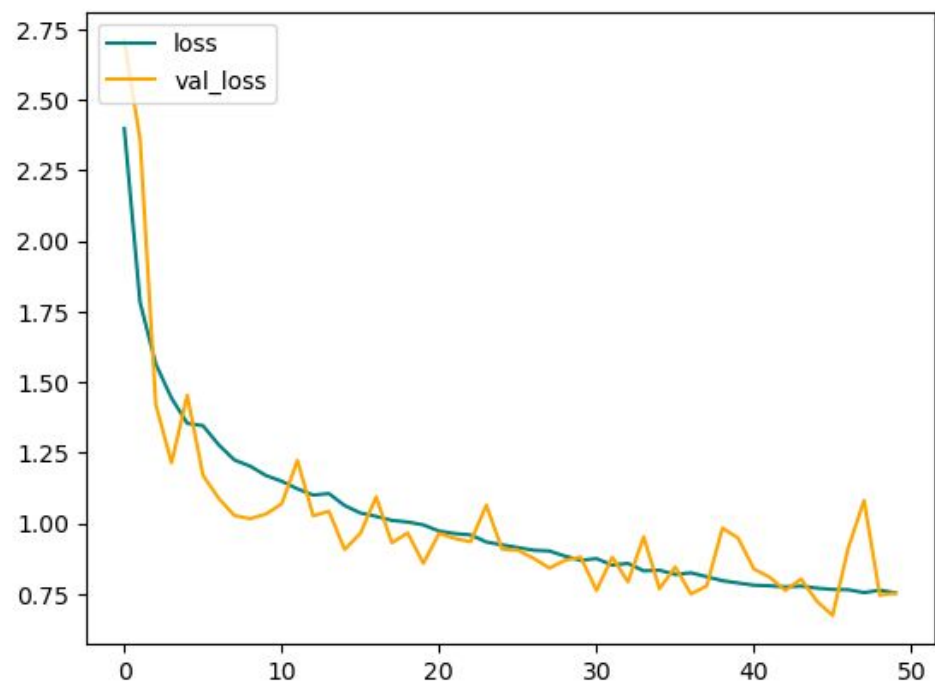
California Poppy



Accuracy

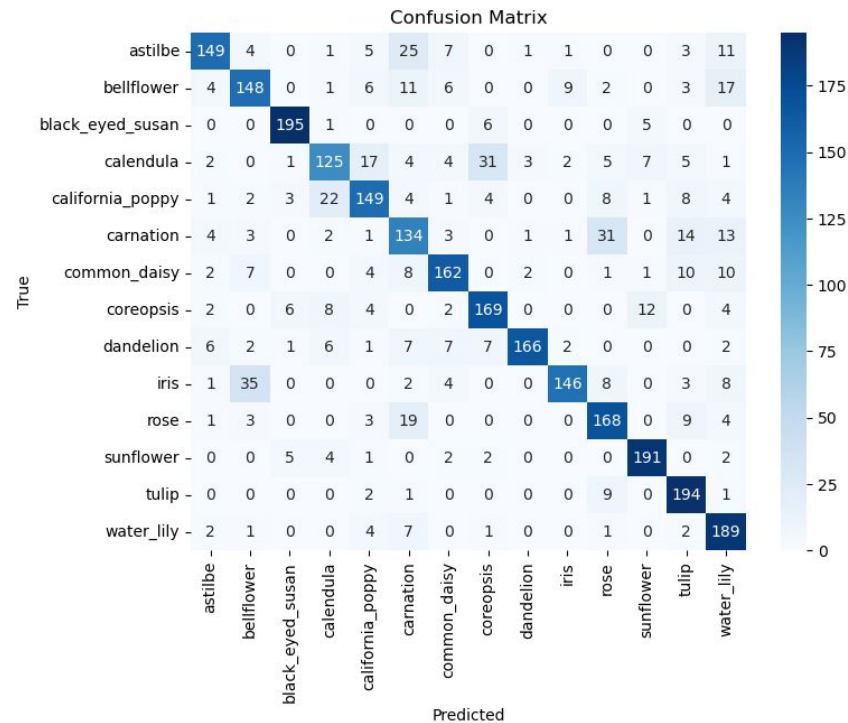


Loss

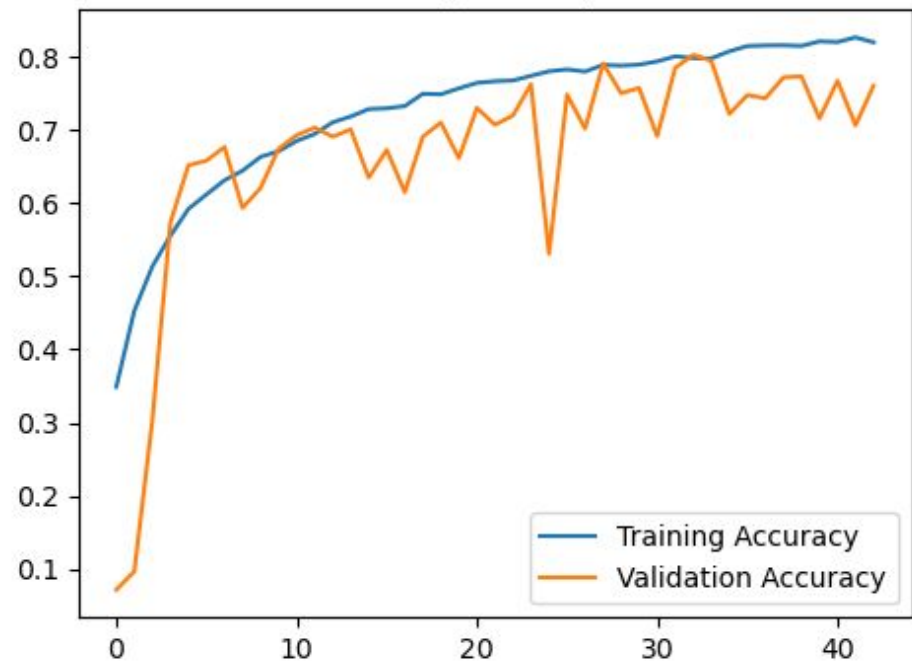


Hyperparameter Tuning

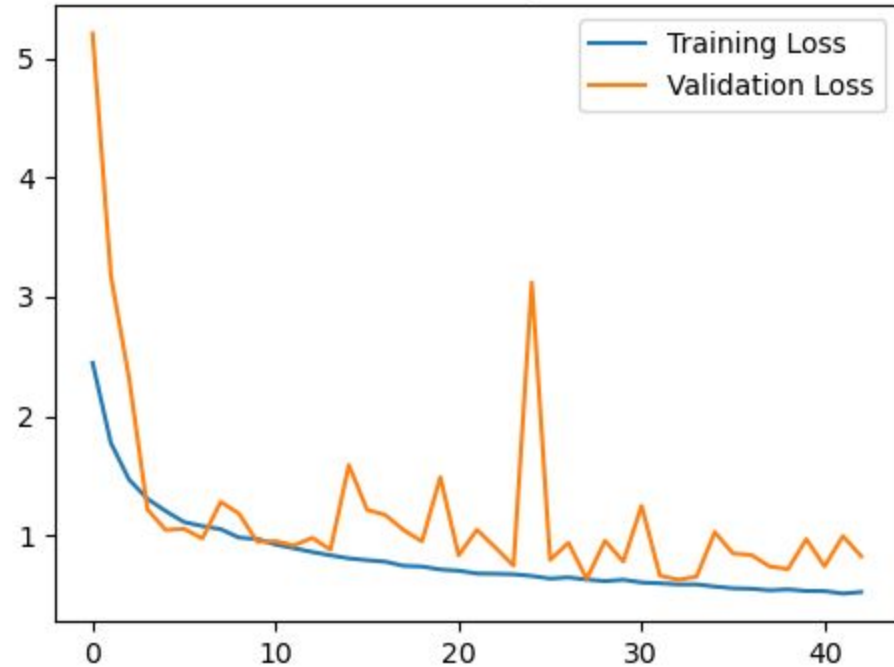
- Improved model accuracy from 76.7% to 78%, a 1.3% increase.
- Integrated callbacks including EarlyStopping and ReduceLROnPlateau.
- Fine-tuned key hyperparameters: units, dropout rates, and regularization rates.



Accuracy over epochs

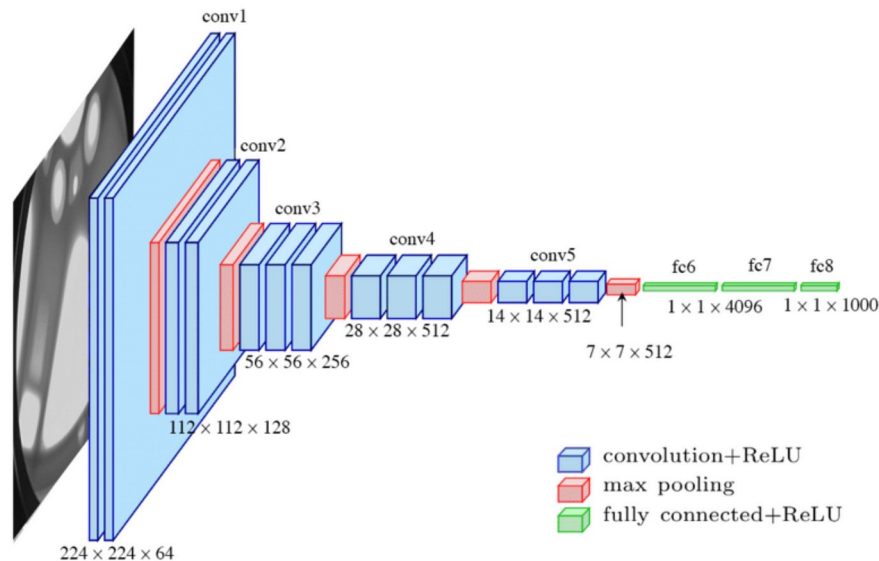


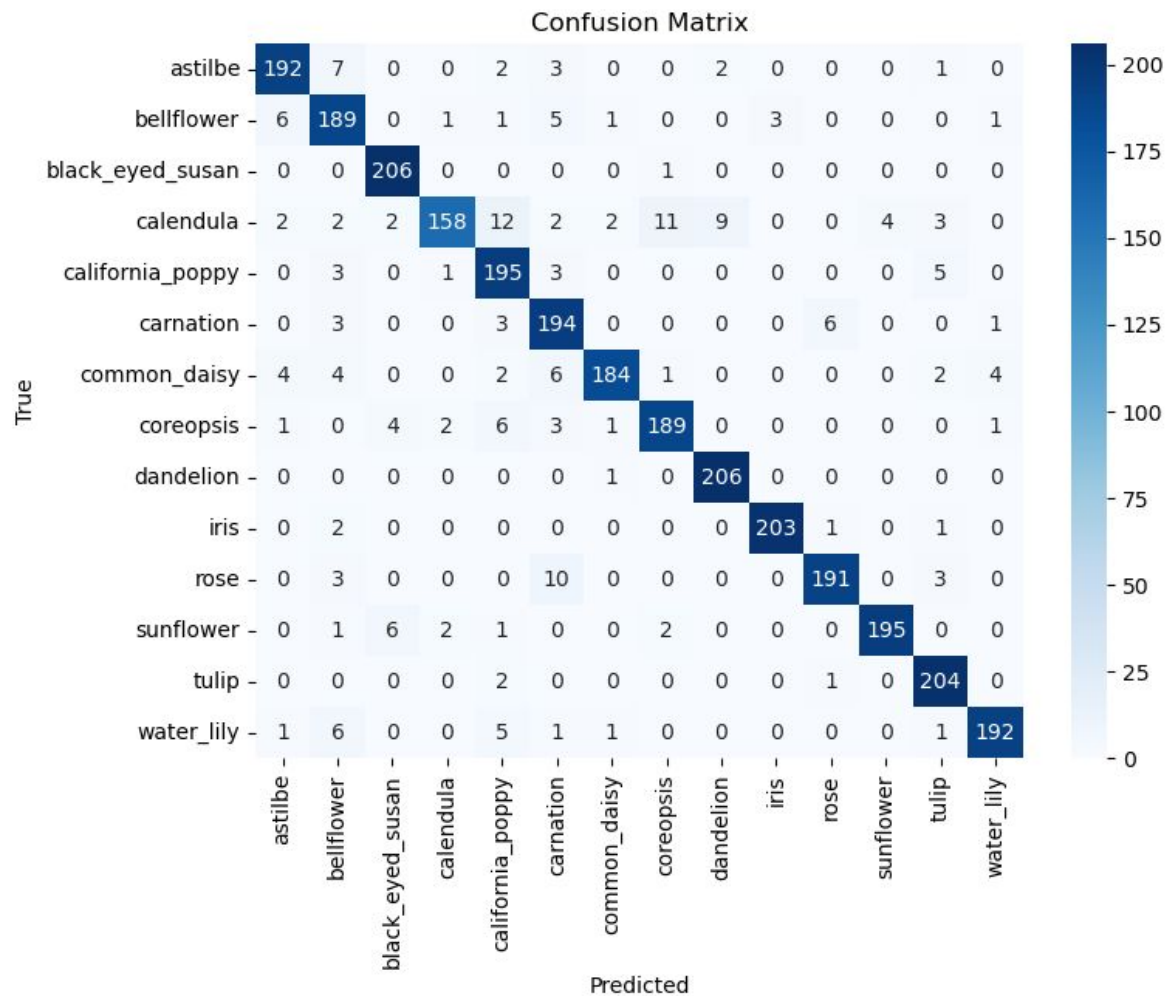
Loss over epochs



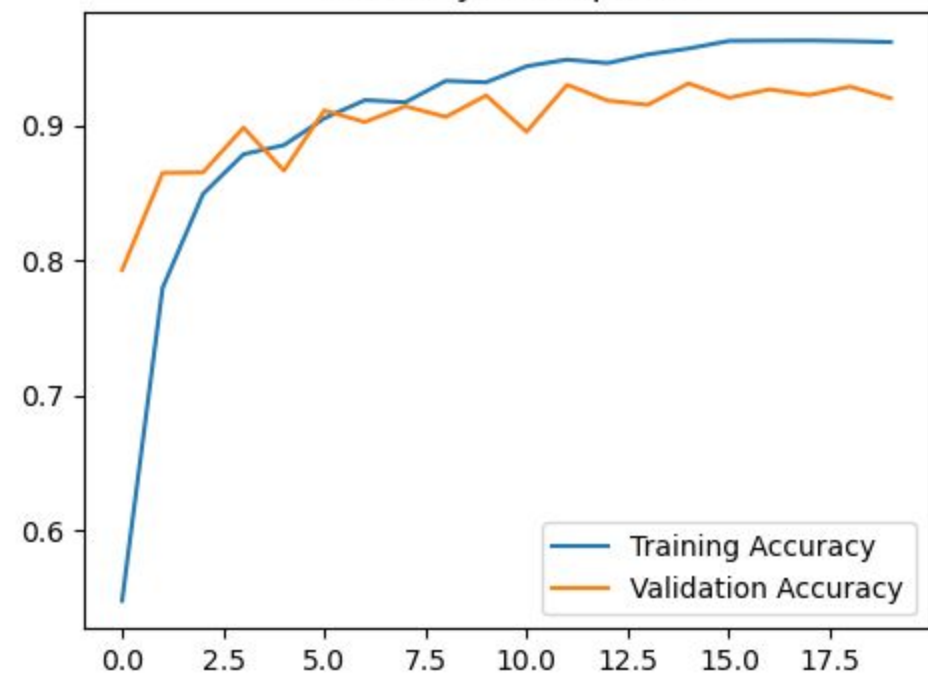
Best Model (VGG16)

- VGG16 is a deep convolutional neural network with 16 weighted layers often used as a benchmark in computer vision.
- Trained from imagenet dataset (14 million images)
- Performed best out of all models when incorporated into our dataset (93.1% accuracy)

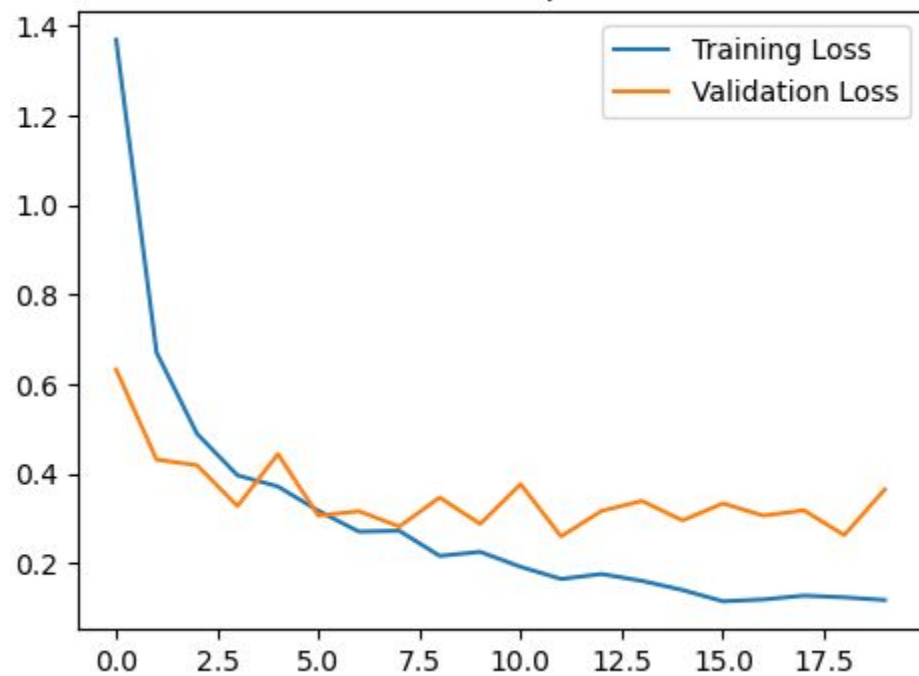




Accuracy over epochs



Loss over epochs



Recommendations:

- Integrate flower recognition in BlossomTech's app for instant flower info, care instructions, and purchase options, boosting customer engagement and sales.
- Implement the technology in BlossomTech's gardening apps for immediate flower identification and care tips, enhancing user experience and customer base.
- Use user interaction data from the flower recognition feature to customize marketing, product recommendations, and shopping experiences on BlossomShop.
- License the flower recognition technology to florists, landscaping firms, and botanical gardens for additional revenue.

Next Steps:

Architecture Modifications:

- Increase Model Complexity: Experiment with adding more convolutional layers, increasing the number of filters, or using deeper neural network architectures. Be cautious not to overfit, and use dropout layers to regularize if needed.
- Adjust Pooling Layers: Try different pooling techniques like AveragePooling2D or GlobalAveragePooling2D instead of MaxPooling2D to capture different features.

Ensemble Learning:

- Combine Multiple Models: Train multiple models with different architectures or hyperparameters and ensemble their predictions. This can help improve overall accuracy

Custom Loss Functions:

- Design custom loss functions that emphasize specific aspects of your task, such as reducing false positives or false negatives, if your dataset has imbalanced classes.

Contact Me:

Franko Ndou

GitHub: <https://github.com/fndou05>

LinkedIn: <https://www.linkedin.com/in/frankondou/>

Email: frankondou@gmail.com